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Distributional impacts of disaster recovery: Sri Lankan households a decade after the 2004 Indian Ocean tsunami

Diana De Alwis

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Further enquiries to:

The Administrator
School of Economics and Finance
Victoria University of Wellington
P O Box 600
Wellington 6140
New Zealand

Phone: +64 4 463 5353
Email: alice.fong@vuw.ac.nz

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Distributional Impacts of Disaster Recovery: Sri Lankan Households a decade after the 2004 Indian Ocean Tsunami

Diana De Alwis
Victoria University of Wellington

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Abstract

This paper investigates the impact of recovery from the 2004 tsunami on income and consumption distribution across households in Sri Lanka, using a quasi-quantile regression method and other inequality measures. The analysis finds that the income of households in the entire distribution has recovered, with low-income households increasing their income by a higher proportion compared to the higher income households. The paper also observes that the affected regions appear more income-equal ex-post compared to the unaffected regions. Household consumption recovered in short and medium-term favoring both high and low-income households compared to those in the middle-income category. Nonetheless, long-lasting recovery of consumption appears only among high income households.

JEL: Q54, R11, I32

Keywords: Sri Lanka, tsunami, households, recovery, inequality

1. Introduction

The purpose of this paper is to estimate the causal impact of recovery from catastrophic tsunami in 2004 on different parts of the income distribution of Sri Lankan households a decade after the event. Distributional impacts of disaster recovery have received considerable critical attention in policy debate, but the empirical literature has not treated this topic in much detail. While standard economic theory suggests a complete recovery in the long term after catastrophic natural disasters (Albala-Bertrand, 1993), other literature finds evidence of the reconstruction process producing higher returns in productivity and higher growth – a recovery that leads to the economy being better off than before (Skidmore and Toya, 2002; Hallegate and Dumas, 2009; Kim, 2010; Jaramillo, 2009). Evidence for potentially successful long-lasting recovery of households a decade after the 2004 tsunami is revealed from a recent study in Sri Lanka (De Alwis and Noy, 2016). Only very few studies attempted to investigate the distribution of such recovery benefits and changes in inequality measures. A limited literature also attempted to determine the distribution of disaster impacts based on pre-existing social physical and economic vulnerabilities (Buia *et al*, 2014; Yamamura, 2015; Karim and Noy, 2016). This void in the literature is the key motivating factor of this paper.

Specific to the observation of Sri Lankan households recovery after the tsunami (De Alwis and Noy, 2016), what is most unclear is whether the observed average household's recovery is equally observed across the entire distribution of affected households. Further, clarity is needed whether the observed recovery is free from negative spill overs such as inequality that can associate with it. In this paper, we aim to describe what happened to the Sri Lankan households long after the catastrophic tsunami. Firstly, this paper investigates the recovery benefits across affected households using quasi quantile regression method. Secondly, we evaluate the impact of recovery on inequality quantitatively using Gini coefficient, generalized entropy measures (GE) and graphically using the Lorenz curve approach. This research uses quasi quantile regression approach using five household income and expenditure survey waves of Sri Lanka (1995, 2002, 2006, 2009, and 2013).

2. Literature

Theoretical literature view complex interaction of factors such as household assets, their ownership, their utilization and return, income generating opportunities available to them and their decisions, the level of their access to public goods, dimensions such as their exclusion, political voice, social capital, and existing institutions and governance structures all determining the level of household income and poverty (Attanasio and Székely, 1999, Carter and Barrett, 2006, Rodriguez -orregea *et al*, 2009; Halligatte *et al*, 2014). By interfering with one or more of these factors and causal channels, the exogenous natural shocks can affect the household's level of income, consumption, and poverty. Disasters can destroy or damage the household's productive assets (physical, natural, financial, public infrastructure etc.) or force households to liquidate their assets to maintain their consumption after the disaster (Kazianga and Udry, 2006; Barrett *et al*., 2006). With limited ability to self-insure and ex-ante disaster risk sharing, households can fall into poverty traps if disasters cause heavy destruction of household assets (Carter and Barrett, 2006). When disasters are large enough to affect the economic or environmental conditions, the returns to household assets can be impaired, for example reduce labour or agricultural land productivity (Food and Agriculture organization [FAO], 2015). Catastrophic disasters with extremely high damage to lifeline resources can also increase the price of food, energy, or land (Cavallo, Cavallo, and Rigobon, 2014; Haraguchi & Lall, 2015) hurting the poor the most.

Empirical literature that investigates disaster recovery reveals that recovery correlates negatively with the extent of property damage to business (Tierney, 1997; Alesch *et al*. 2001; Chang and Falit-Baiamonte, 2002; Lam *et al*. 2009), however businesses with little damage but with highly damaged neighbourhoods often find difficulties to recover due to loss of customers (Webb, Tierney and Dahlhamer, 2000; Chang and Baiamonte 2002). Delays in Infrastructure restoration can be a significant barrier to businesses re-opening (Webb *et al*. 2000, 2002; Lam *et al*. 2009) and some types of businesses, sectors, and local economies tend to have greater difficulty to recover from disasters than others (Dahlhamer and Tierney, 1998; Alesch *et al*. 2001; Chang and Falit-Baiamonte, 2002). Relocations after disasters in certain instances can limit the income opportunities to settlers compared to pre-disaster (Arnal *et al*, 2013). The exclusion of households - based on gender, ethnicities etc. - from the reconstruction such as access to reconstruction aid can also limit the income opportunities of affected households leaving such households in poverty (Aldrich, 2010; Becchetti and Castriota, 2011, Kammerbauera and Wamslerb, 2017).

Only few studies attempted to reveal causal connection of recovery and distribution impacts. In a cross-country study, Cuaresma *et al* (2008) observe that natural disaster recovery benefits negatively associate with low income. Landry *et al* (2007)'s study investigating the return migration decisions of the evacuees of 2005 hurricane Katrina in the Unites States from the Gulf region finds that higher proportion of middle income families is planning to return and the low income families have low willingness to return. Fussell (2015)'s review of research on mobility - evacuation and migration - long after Katrina supports the contention that disaster driven migrants are more likely among minorities and economically disadvantage people. This research also finds that recovery for different segments of the population is driven by different mechanisms. Shaughnessy, White and Brendler (2010) analyse the income distribution effect of hurricane Katrina in New Orleans short and long time after the event using income density function approach - New Orleans and the United States pre-and post-event. It is evident that the event causing the income distribution to push towards the higher income groups in long term and suggestive of high skilled in-migrations after the disaster. Munoz and Tale (2016) investigate distribution of recovery funds for flood damaged property acquisition after 2008 Midwest flood in Iowa State in the United States using spatial econometric modelling. The research finds that the households in high social vulnerability areas were less likely to receive full financial compensation and endure longer period for receiving acquisition funds. Lower recovery rates of the damaged property are observed from the areas with high number of elderly and Hispanic residents.

3. Sri Lanka Context

Sri Lanka is a lower middle-income country with per capita income of 13,800 US$ (PPP) (World Bank, 2016). Out of 21.2 million people, 4.1% live below the national poverty line

(Department of Census and Statistics, 2016). In 2004, the catastrophic Indian Ocean tsunami caused 35,500 lives lost and more than one million people affected. Infrastructure facilities - houses, public buildings, hospitals, hotels, fishery harbours, roads, railways, power, telecommunication, water supply and sanitation facilities - were severely damaged and the overall economic losses totalled USD 1.5 billion, approximately 5% of the country's GDP (Department of Census and Statistics, 2005). Thirteen coastal districts out of 14 coastal districts in the country were affected and tourism and fisheries were the most seriously affected sectors; 75000 people engaged in fishing lost their main income and tourism sector experienced 20% lower earnings and 3% fewer arrivals[1] in 2005 as compared to pre-tsunami (Ministry of Environment, 2009).

The reconstruction after tsunami in Sri Lanka was planned and coordinated through a special institutional structure: The Task Force to Rebuild the Nation (TAFREN), later renamed as the Reconstruction and Development Agency (RADA) (GoSL, 2005, 2006). The government of Sri Lanka estimated the total reconstruction investment need of 2 billion USD including an ambitious build back better long-term reconstruction program (GOSL, 2005). The rebuilding after the tsunami was financed mainly by external aid and loans. Most of the funds were allocated for housing (45%), livelihood (18%) and the rest for asset replacement (Swedish International Development Agency [SIDA], 2009). Reconstruction activities were undertaken under the special programs until 2008 and the remaining activities were undertaken later under the government development program. Due to the pressure to satisfy beneficiary expectations, the reconstruction was accelerated (Khasalamwa and Boano, 2009) and reconstruction in south and west in the country - the treatment districts in this paper - was basically completed by the end of 2008 (Jayasuriya and McCawley, 2010).

4. Methodology

[1]This is a remarkably small decrease in arrivals as compared to the reduced earnings from the tourism sector in the post disaster. The tourist arrivals account for every single visit with at least a single overnight stay in the country. International aid played a major role in the post disaster reconstruction in Sri Lanka and aid agency staff visiting the country after the disaster were most likely included in these counts.

We use the quasi quantile experimental (diff-in-diff/DID) method to isolate the distributional effect of tsunami recovery. Unlike linear regression model that estimates the conditional expectations of outcome, the quantile regression model (Koenker and Bassett, 1978, Chernozhukov and Hanses, 2006) estimates the outcome at a different point in the conditional distribution which is a linear function of the covariates. The model specification takes the form below.

$$q^{\tau}Y_{idt} = \beta_1^{\tau} + \beta_2^{\tau}Post_iT_d + \beta_{3_3}^{\ \tau}\,\delta_t + \beta_4^{\tau}X_{idt} + \beta_5^{\tau}\gamma_d + U_{idt}^{\tau}$$

$q^{\tau}Y_{idt}$ is the outcomes of interest (household monthly consumption and household monthly income) at τ th quantile. The unit observed is household *i,* in district *d* and time *t*. T_d is the treatment dummy defining membership in the treatment cross section (affected=1, not affected=0) and U_{idt} are the unobserved affects. The treatment group is defined for households in seven affected districts (Colombo, Gampaha, Kalutara, Galle, Matara, Hambantota and Puttlam). $Post_i$ is a dummy variable to distinguish the sample by pre- and post-treatment. β_2 is the coefficient of interest to isolate the treatment effect. As the treatment effects are naturally heterogeneous across households depending on their characteristics, the household socio economic and demographic characteristics (X_{idt})are used in the model to control for such heterogeneity

To isolate the causal effect, the quasi quantile regression approach relies on the standard quasi regression parallel trend assumption. The treatment effect in each quantile is precisely identified only if the treatment and control group in each quantile have parallel trend before the treatment event. Then for any fixed percentile, the estimated treatment effect in quantile regression is the horizontal distance between two cumulative distribution functions of treatment and control groups. Thus, isolation of QTE at individual level (household) also relies on rank preservation assumption: relative value of -rank-of the potential outcome for a given individual to be the same regardless of whether that individual is in the treatment or in the control groups. The rank preservation assumption could be unreasonable if treatment correlates with unobserved covariates and change the rank order of households post disaster period. The change-in-change approach (CIC) is an alternative method of isolating the quantile treatment effect (Athey and Imbens, 2006; Melly, and Santangelo, 2015). It relaxes the parallel trend assumption of the quasi quantile regression method but still maintains the rank preservation assumption. Athey and Imbens' method recovers the whole distribution of the counterfactual outcome; its estimation is relatively straightforward in the absence of covariates. A recent method proposed by Melly and Santangelo (2015) suggests a semi parametric estimator that also can include covariates. The validity of these assumptions in this study is discussed in detail in the robustness analysis section.

This study applies both conditional (CQTEs) and unconditional (UCQTEs) quantile regression with diff-in-diff specification of the model to isolate the treatment effect on each quantile. In conditional quantile estimation regression, the placement of the households across quantiles is based on the error term after controlling for the covariates (outcome distribution conditioned on the mean of the other covariates). The conditional quantile estimates can be interpreted as the relationship of the treatment variable with the conditional outcome distribution. This study uses the Parente and SantosSilva (2016) method to estimate the standard errors that are robust to heteroscedasticity and intra-cluster correlation.

However, the unconditional quantile estimations are more practically useful for policy purpose than conditional quantile estimates. We estimate unconditional quantiles using the Powell (2017)'s generalized Quantile regression (GQR) method. This method estimates the standard errors where treatment effects are "conditional" on the treatment variables but unconditional on the "control variables". Thus, UCQTEs are interpreted as the relationship of treatment to unconditional outcome distribution and therefore our inferences mainly rely on the UCQTEs.

The empirical literature use Lorenz curve and Gini coefficients widely and some studies use probability density function (Madden, 2000, Campano and Salvatore, 2006, Shaughnessy, White and Brendler, 2010) to measure distributions. To evaluate the impact of tsunami recovery on income/consumption distribution, we calculate the Gini coefficient for treatment regions, control regions and the whole sample during pre-and post- disaster periods. We then compare the extent of deviation of income/consumption distribution from perfect equality in pre and post disaster periods. The paper also estimates the coefficient of variation, a measure which is more sensitive to the changes in the upper tail. Since the household income data has negative values (our household income measure part of the total household income. See the appendix table 1), we estimate Gini coefficient both with and without zero and negative values. We plot the Lorenz curve to show the distributional effects graphically.

Our data come from the five national household income and expenditure surveys of 1995, 2002, 2006, 2009 and 2013 in Sri Lanka. The treatment group comprises seven affected districts out of total 13 affected districts. The other tsunami affected coastal districts that were directly affected by the internal conflict and no data is available about them for the household surveys.

5. Results

Table 1 presents the summary statistics. Table 2 and 3 show the estimates of income and consumption recovery in each quantile respectively using both conditional and unconditional quantile regression methods for three post recovery years. In conditional quantile estimates, we study how tsunami recovery vary for household income/consumption given observed characteristics whereas in unconditional quantile regression we explore whether the recovery varied depending on the observed income/consumption. The log normal quantile regression models are also estimated to evaluate the elasticities. The results are reported in percentage column in tables 1 and 2.

The summary statistics in the table 1 show that the households in all quantiles are almost similar according to the household characteristics such as gender and age of the household head and the ethnicity (column 3, 4 and 7 respectively). The households in the lowest and highest quantiles appear smaller in size (column 6) compared to the households in the middle quantiles. Considering the exposure to the tsunami disaster, our treatment group has higher representation from the high-income households compared to the households in the lowest quantiles (column 8). It also appears that there is a higher representation of households in the post tsunami from the higher and the lower quantiles compared to those in the middle quantiles (column 9).

Income recovery distribution

Conditional quantile regression

Table 2 presents the recovery across the income quantiles. The conditional quantile regression results are given in the results columns 1-6. The estimates in the column 1 show significant income (except the lowest quantile) increase across quantiles favoring the highest quantiles more compared to the lower quantiles. Similar observations are made considering the percentage scale in the column 2. These results indicate that high-income households -as conditioned on observed characteristics - are better off than the household in the lower quantiles in the year just after the disaster. This clearly indicates that the recovery in the first post disaster is biased to rich. Similar pattern appears in the column 3 and 5 for other post disaster years. Considering the long-lasting recovery of households in each quantile, all quantiles show a decline of recovery benefits in year 2009 and again increase in 2012 similarly to the variation of recovery of the average household reported by De Alwis and Noy (2016). Nevertheless, recovery in percentage scales in column 4 and 6 are inconsistent. For example, third and fourth quantile show a negative recovery considering the percentage scale but positive for absolute income. This possibly could be due to non-linearity of outcome in difference in difference model.[2]

These results show that, the recovery from this catastrophic disaster is positively skewed to rich households when households are ranked conditional on education, age, ethnicity, sex, and geographical location. The conditional estimates reveal more unequal treatment effect on a similar household groups on observed factors.

Unconditional quantile regression

The unconditional quantile regression estimates are presented in the 7-12 results columns of the table 2. The first year of the post disaster (2006) in column 7 shows a "U" shape distribution of recovery across income quantiles; higher significant recovery benefits accrued to the lowest income quantile (12121 SLR) and then reduction across quantiles up to 5th quantile (4126 SLR) and increasing benefits to high income groups

[2] Melly, and Santangelo (2015)'s changes-in-changes model remedy the more restrictive assumptions in difference-in-difference quantile method including the linear difference in difference model.

(19956 LKR for 99th percentile). The recovery in the years 2009 and 2012 (column 9 and 11 respectively) show that the recovery in the lowest income quantile is not sustained and higher income groups show better recovery with much higher benefits compared to lower quantiles in both post disaster years. Similar to the reported average household recovery, all income group's recovery plummeted in 2009 - the year that government intensified fighting with LTTE. The post disaster periods 2009 and 2012 (in column 9 and 11) show much higher benefits to high income groups and is suggestive of more widening of recovery gap between rich and poor later in the post disaster years (figure3). However, elasticity of income recovery estimates in 2006 (column 8) show inverse relationship of recovery across quantiles; proportion of income recovery for low income groups is higher (9.4%) and it is getting lower along up to high income groups (0.43 % in the 99th percentile). A similar pattern is observed for the post disaster years 2009 and 2012 except the lowest quantile and households in the 99% of the income distribution (in the column 10 and 12). Deviating from the observed pattern of other quantiles, the income recovery of the household in the lowest quantile turn to totally opposite direction and recovery of the households in the 99 % of the income distribution stays lower than the 9th quantile in both 2009 and 2012. Again, distribution of recovery benefits across post disaster years shows a drop in the year 2009; these results are depicted in the figure 4.

Consumption recovery distribution

Conditional quantile regression

Table 3 provides the consumption recovery across quantiles. The conditional quantile estimates are given in column 1-6. The most recent post disaster observation (year 2006 in the column 1) shows an increasing benefit across quantiles towards the highest quantiles as observed for the income recovery (334 -8975 LKR). The other post disaster years 2009 and 2012 in column 3 and 5 respectively show a similar pattern (except highest quantile in year 2012). The recovery across almost all quantiles is statistically insignificant in 2009. Even though there is a decline of consumption in 2009, the recovery in 2012 is higher than the recovery achieved in the year 2006 (column1 and 5). The consumption recovery across post disaster years again shows a similar pattern of the income recovery (column 1, 3, 5).

However, a nuanced picture appears when log normal model is used; negative consumption recovery is observed as opposed to non-log model and most of the estimates are statistically insignificant.

Unconditional quantile regression

Unconditional regression estimates show a "U" shape distribution of consumption recovery across lowest to highest quantile in post disaster years 2006 (823, 12907LKR in column 7) and 2009 (483, 4550 LKR in column 9). Figure 5 shows the observed consumption recovery across quantiles in each year. Similar "U" shape curve is revealed in the estimates as percentage of consumption for these post disaster years (22%, 24% in column 8 and 13%, 9% in column 10). Figure 6 shows the observations for post disaster years 2006 and 2009. In the post disaster 2009, the households in the lowest and the highest quantile's recovery (except the negative recovery in the 6^{th} quantile) only are statistically significant (column 10). Further, in the latest post disaster year 2012, the recovery among middle quantiles is also statistically non-significant and it is sustained only among the higher quantiles (column 12). Recovery in the higher quantiles (8^{th} onwards) in 2012 bounce back to the level of the first post disaster year or even further extended after a reduction in year 2009. This recovery pattern is similar to the observed income recovery among almost all quantiles.

Inequality of income and consumption

The inequality measures for the whole sample and separately for the treated and control districts over the survey periods are given in the Figure 1 and 2 (a and b) respectively. The Gini coefficient of household income for the whole sample (figure 1) shows an increase of inequality in 2002 compared to the year 1995 then a reduction in the first post disaster year 2006. Again, an increase and reduction of Gini coefficient is observed respectively in year 2009 and 2012. However, the inequality in 2012 remains higher than the inequality in 1995. The coefficient of variation, which is more sensitive to the higher income groups shows similar trends, but the coefficient in 2012 is lower than 1995. In contrast to income, the Gini coefficient for consumption shows an increase of inequality up to the first post disaster year and then decline in later post disaster years. The latest is still higher than the year 1995. The coefficient of variation for consumption also shows a reduction during post disaster years and in the recent year remains lower than in 1995. These results clearly show an increase of inequality in the first post disaster year and then a reduction of inequality across the post disaster years.

Comparing the income of tsunami affected and not affected households separately in the Figure 2 (a and b), the affected region (Figure 2 a) appears more equal than the unaffected regions. Comparing the two groups in the pre and post disaster years, the affected region's income inequality increased from 1995 to 2002, but reduced in the post disaster period and ended up lower than the first survey year. In contrast, the non-affected region's inequality increased over the survey years. The coefficient of variation (figure 2 b) shows a similar pattern of Gini coefficient for both groups. The results indicate a reduction of inequality in affected compared to unaffected regions during the post tsunami period.

In contrast, the Gini coefficients (in Figure 2 a) show that the affected regions are more unequal in consumption than the non-affected regions in the first survey year. Both group's inequality is increased up to 2002, but the inequality among the unaffected regions is increased compared to affected regions in the first post disaster year 2006. Then it is reduced for both groups over the post disaster years; more importantly, the affected region's Gini coefficient remains lower than the not affected region in the recent post disaster year 2012. The coefficient of variation follows an almost similar pattern for unaffected regions but affected regions show a reduction of Gini coefficient across post disaster years (Figure 2 b). It again shows affected regions becoming more equal after the tsunami. These observations are also depicted in the Lorenz curves in appendix figures 3 to 8.

6. Robustness analysis

Our quantile estimates are reliable only if each pair of treatment and control quantile show a parallel trend during the pre-disaster period as required for quasi experimental methods. To check the validity of this assumption, a placebo test analysis was conducted for each quantile treating the treatment group a year prior to the treatment (Using the treatment and year 2002 interaction variable). The results are given in the table 4. The coefficients revealed for both income and consumption for all quantiles are not statistically significant providing evidence for the validity of parallel trend assumption. Further, normalized income for selected quantiles (2nd, 5th, 7th and 9th quantiles) in figures 7, 8, 9, and 10 show a much closer trend of the residual income between the two groups during pre-disaster period. Similar observations appear for normalized consumption of households in figures 11, 12, 13, and 14. Alternatively, we estimated quantile treatment effects using change in change (CIC) estimation method of Melly and Santangelo (2015). Our estimations in the quasi quantile regression seem reliable as a similar pattern of income recovery revealed in the change in change method. [3] Despite that the change in change approach relax the parallel trend assumption, the rank preservation assumption is still not eliminated.

Further, conditional, and unconditional quantile estimates are still not reliable if the rank preservation assumption is not held. Violation of this assumption is possible in this case if the treatment correlate with any other time varying unobserved factors and as a result if the households in the first post disaster year are placed in a different quantile (higher or lower) in the later post disaster years. Given the increased income due to the tsunami (as revealed by De Alwis and Noy, 2016), it is likely to place the low-income households in high income quantiles in the post disaster period. Our analysis is not able to observe such rank position shift as our survey data is cross sectional. If rank position is violated, the observed higher income/consumption gains to the high-income quantiles in the post disaster years in this study could be due to shift of the lower income household's rank position up in the distribution in the later post disaster years than treatment effect on the households in high income quantiles.

7. Conclusions

[3] The change-in-change estimations will be available on request from the author. We thank Professor Blaise Melly for generously sharing the CIC Stata codes. As work on this method is still in progress, we are unsure of the validity of our estimates using this method.

This study set out to determine the distributional impacts of catastrophic Indian Ocean tsunami in Sri Lanka. Considering both observed and conditional income groups, the income recovery from catastrophic tsunami in Sri Lanka shows a positively skewed distribution to rich households; the recovery biases to rich is further increased and persistent over time. The household consumption recovery also follows a similar pattern. However, contrasting evidence emerges when recovery is estimated as a percentage of average income for observed income groups. The recovery of income among almost all income groups is sustained even a decade after the event; the recovery is positively skewed to the low-income households (in relative terms). It is further evident in the observed inequality measures.

A somewhat different picture emerges for consumption recovery. Estimates of recovery as a percentage of average consumption show "U" shaped recovery[4] across all groups - poor to rich - in the short and medium term. All groups recovered in the short term, recovery of the households in the middle of the distribution fades away in the medium term and recovery is persistent only among the rich groups in the long run. Overall, this observation is suggestive of an increase in consumption inequality in the affected regions in the long term.

A number of caveats need to be noted regarding the present study. For instance, one source of weakness which could have affected the measurements in our quasi quantile analysis is the rank preservation assumption. The current study is limited by the cross-sectional design and unable to examine this variation.[5]

[4] Past studies reveal that poor are observed with higher direct damage due to high vulnerability and exposure to disasters and also higher value of damage to rich as they possess expensive assets

[5] Shift of the low-income household's rank position up in the distribution in the later post-disaster years is likely in this case as the poor achieved significantly more recovery shortly after the disaster. As a result, the observed recovery of the higher quantiles in the later post disaster years could be misleading. It is possible that the rich favored recovery revealed in the latest post disaster years rather emphasizes the sustenance of the recovery achieved by the poor households in the first post disaster year.

Other limitation need mention is that the results are valid only in absence of spill-over effects between affected and not affected regions which has not ruled out yet in the analysis. Further work is required to establish better accuracy for the causal identification and to establish the causal story for our observations.

Table 1 Summary statistics for quantiles

Income quantile	Total Income in SL Rs.	Total consumption in SL Rs.	Sex of Household head (Male)	Age of Household head	Years of education of the Household head	Household size	Ethnicity Singhalese	Proportion of affected households	Proportion of household's post tsunami
1	-41	7870	.80	48	6.8	4.3	.80	.18	.44
2	8	9813	.76	50	7.1	4.2	.77	.12	.87
3	93	11880	.79	50	7.2	4.3	.85	.10	.82
4	1519	8190	.79	50	6.8	4.5	.85	.46	.20
5	3358	8915	.78	51	6.9	4.6	.81	.58	.31
6	5171	9658	.77	51	7.1	4.6	.81	.62	.42
7	7559	10848	.77	51	7.2	4.6	.81	.67	.55
8	11088	12801	.76	52	7.4	4.6	.79	.73	.68
9	17093	14743	.76	51	7.5	4.5	.80	.81	.80
10	37294	18790	.76	51	8.1	4.4	.81	.90	.90
Average	8310	11244	.78	50	7.2	4.5	.81	.52	.57

Table 2 Income recovery across quantiles

Year Quantile	Conditional (cluster bootstrap) QR						Unconditional (Robust) QR					
	2006	**%**	**2009**	**%**	**2012**	**%**	**2006**	**%**	**2009**	**%**	**2012**	**%**
0.1	2601 (1673)	0.84 (0.26) ***	2616 (1525) *	0.81 (0.22) ***	5033 (2997) *	0.77 (0.27) ***	12121 (53) ***	9.40 (0.01) ***	-4301 (66) ***	-66.7 (0.18) ***	-1507 (43) ***	-12.7 (0.05) ***
0.2	3114 (1238) ***	0.80 (0.35) ***	3059 (1179) ***	0.08 (0.27)	6760 (2700) ***	0.13 (0.24)	4847 (2) ***	9.65 (0.006) ***	90 (5) ***	7.03 (0.005) ***	10071 (2) ***	8.82 (0.001) ***
0.3	3297 (1236) ***	0.89 (0.39) ***	3289 (1123) ***	-0.12 (0.32)	8572 (3048) ***	-0.03 (0.30)	7510 (171) ***	5.5 (0.01) ***	3883 (54) ***	4.6 (0.02) ***	3734 (306) ***	4.9 (0.02) ***
0.4	3489 (1395) ***	1.10 (0.38) ***	3477 (1237) ***	-0.26 (0.48)	10466 (3041) ***	-0.11 (0.43)	5167 (294) ***	1.82 (0.14) ***	4617 (256) ***	1.72 (0.13) ***	10582 (439) ***	2.45 (0.13) ***
0.5	3767 (2056) *	2.25 (1.40)	3486 (1309) ***	0.15 (0.88)	12378 (3722) ***	0.28 (0.84)	4126 (178) ***	0.87 (0.3) ***	3913 (129) ***	0.84 (03) ***	9883 (240) ***	1.5 (0.3) ***
0.6	4353 (2220) ***	2.92 (3.69)	3293 (1822) ***	0.46 (0.84)	14499 (3901) ***	0.57 (0.90)	8922 (33) ***	0.72 (0.02) ***	5838 (137) ***	0.71 (0.02) ***	13068 (276) ***	1.24 (0.02) ***
0.7	5350 (2490) **	1.65 (1.49)	3853 (1847) **	0.72 (0.80)	17154 (5004) ***	0.86 (0.78)	5726 (211) ***	0.64 (0.02) ***	5610 (179) ***	0.63 (0.02) ***	12691 (252) ***	1.10 (0.02) ***
0.8	6746 (2886) ***	1.64 (1.36)	4679 (2098) **	1.24 (0.93)	20641 (4961) ***	1.33 (0.93)	7711 (233) ***	0.61 (0.02) ***	6803 (188) ***	0.55 (0.01) ***	15367 (233) ***	0.98 (0.01) ***
0.9	9578 (2769) ***	2.08 (1.74)	5977 (2207) ***	1.88 (1.74)	26473 (4812) ***	1.94 (1.45)	9958 (299) ***	0.53 (0.01) ***	8274 (267) ***	0.46 (0.01) ***	20909 (749) ***	0.90 (0.01) ***
0.99	16586 (4846) ***	2.95 (1.33) ***	11321 (5705) *	2.92 (1.14) **	34264 (4706) ***	2.77 (1.78) ***	19956 (688) ***	0.43 (0.003) ***	14779 (65) ***	0.39 (0.002)	34844 (359) ***	0.64 (0.004) ***
Average Treatment effect	7022 (2898) *** [879, 13165]		5787 (2474) *** [543, 11032]		15066 (4802) *** [4887,25245]							
Gini Coefficient of affected districts	0.48		0.46		0.43							

Notes: Robust standard errors in the bracket. ***, **, *, stand for significance at 1%, 5% and 10% respectively. There are 84393 observations. Household covariates include sex, age, years of education, ethnicity of the household head, and household size. The household income (outcome variable of interest) include only paid, agricultural and non-agricultural income, remittances, transfers, dividends, property rents and cash receipts and exclude loans, sale of assets, withdrawal of savings, insurance compensation and other adhoc gains (see appendix 1).

Table 3 Consumption recovery across quantiles

	Conditional (cluster bootstrap method) QR						Unconditional (robust) QR					
Year Quantile	**2006**	**%**	**2009**	**%**	**2012**	**%**	**2006**	**%**	**2009**	**%**	**2012**	**%**
0.1	344 (166) **	0.05 (0.06)	26 (140)	-0.02 (0.04)	769 (531)	-0.04 (0.04)	823 (71) ***	0.22 (0.02) ***	483 (226) **	0.13 (0.01) ***	-23683 (25861)	-43.6 (58.9)
0.2	537 (205) ***	0.05 (0.05)	54 (154)	-0.03 (0.04)	1192 (733) *	-0.05 (0.04)	1017 (53) ***	0.21 (0.01) ***	408 (56) ***	0.09 (0.01) ***	-69330 (44010)	-40.16 (47.58)
0.3	732 (248) ***	0.06 (0.05)	87 (171)	-0.04 (0.04)	1776 (863) **	-0.05 (0.04)	936 (86) ***	0.16 (0.01) ***	191 (63) ***	0.03 (0.01) ***	-32871 (25298)	-87.6 (130.1)
0.4	908 (306) ***	0.06 (0.05)	144 (193)	-0.05 (0.04)	2131 (915) ***	-0.06 (0.03) *	916 (104) ***	0.13 (0.01) ***	129 (91)	0.02 (0.01)	-33984 (32039)	29.4 (21.8)
0.5	1213 (354) ***	0.06 (0.05)	121 (230)	-0.06 (0.03) *	1544 (582) ***	-0.08 (0.04) **	856 (132) ***	0.10 (0.01) ***	-87 (85)	0.01 (0.01)	-54275 (35060)	73.1 (113.1)
0.6	1470 (335) ***	0.06 (0.04)	170 (221)	-0.06 (0.03) *	2875 (1218) ***	-0.10 (0.04) ***	2970 (2238)	0.09 (0.02) ***	673 (803)	-0.006 (0.01)	-1459 (1283)	-0.32 (0.03) ***
0.7	2019 (567) ***	0.07 (0.06)	283 (258)	-0.06 (0.03) *	3212 (1164) ***	-0.11 (0.04) ***	2317 (749) ***	0.14 (0.2) ***	648 (259) ***	0.04 (0.01) ***	299 (239)	0.01 (0.01)
0.8	2777 (632) ***	0.07 (0.05)	646 (321) **	-0.04 (0.03)	4294 (1861) *	-0.09 (0.05)	3142 (259) ***	0.19 (0.02) ***	1395 (212) ***	0.09 (0.01) ***	2571 (146) ***	0.16 (0.01) ***
0.9	3658 (817) ***	0.06 (0.06)	1159 (726)	-0.04 (0.04)	5560 (1819) ***	-0.11 (0.07)	5237 (404) ***	0.23 (0.02) ***	2616 (342) ***	0.12 (0.02) ***	5896 (133) ***	0.26 (0.01) ***
0.99	8975 (2231) ***	0.04 (0.10)	2637 (2690)	-0.08 (0.08)	-43 (2536)	-0.21 (0.11) *	12907 (947) ***	0.24 (0.12) ***	4550 (799) ***	0.09 (0.02) ***	12045 (265) ***	0.22 (0.01) ***
Average treatment effect	1343 (735) * [-214, 2902]		333 (500) [-727, 1392]		2981 (925) *** [1020,4941]							
Gini Coefficient of affected districts	0.37		0.36		0.34							

Notes: Robust standard errors in the bracket. ***, **, *, stand for significance at 1%, 5% and 10% respectively. There are 84393 observations. Household covariates include sex, age, years of education, ethnicity of the household head, and household size. The consumption (outcome variable of interest) is composed of food and non-food expenses and exclude the household investment on durable assets (land, houses, machinery etc.)

Table 4: Robustness check (Placebo test)

Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99
Income	-1156 (2043)	-378 (486)	190 (446)	24 (405)	76 (445)	358 (338)	525 (466)	342 (934)	-257 (1758)	7800 (11014)
Consumption	-28 (280)	-165 (248)	-280 (333)	-278 (399)	-237 (418)	-410 (438)	-436 (505)	-308 (589)	-691 (725)	-1715 (2832)

Figure 1 Inequality indices in all districts

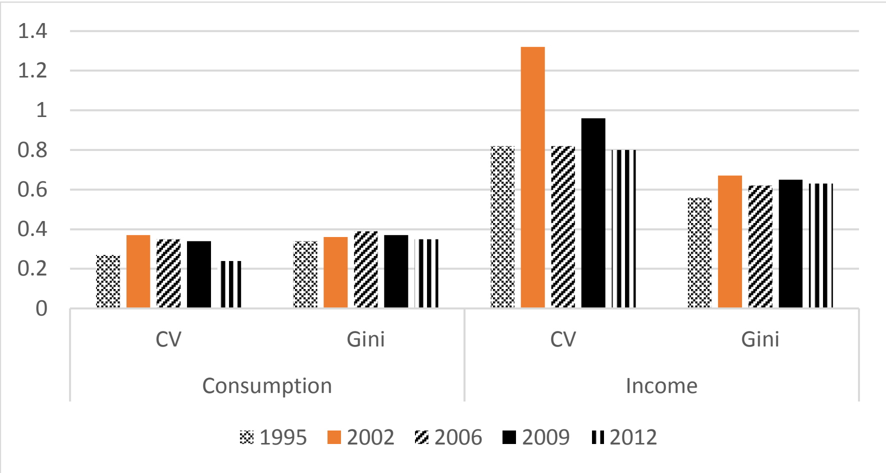
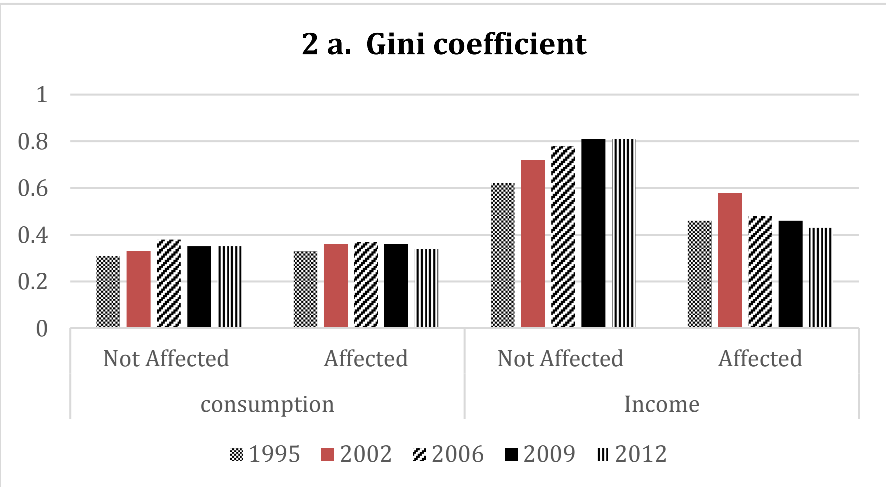


Figure 2 Inequality indices in affected and not affected districts



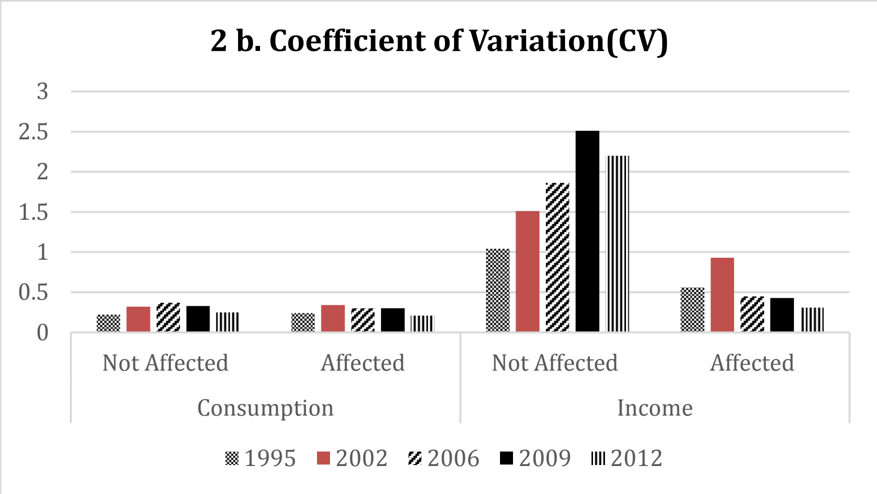


Figure 3

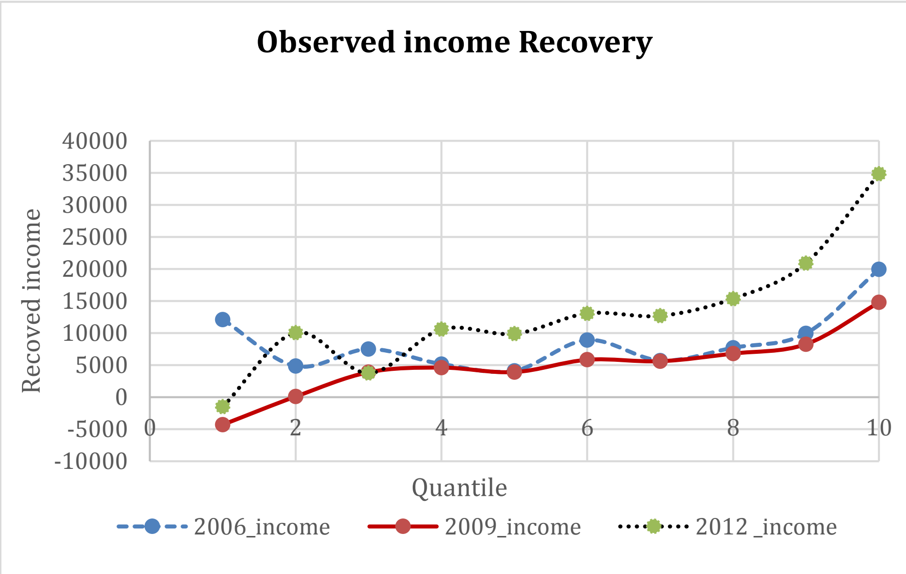


Figure 4

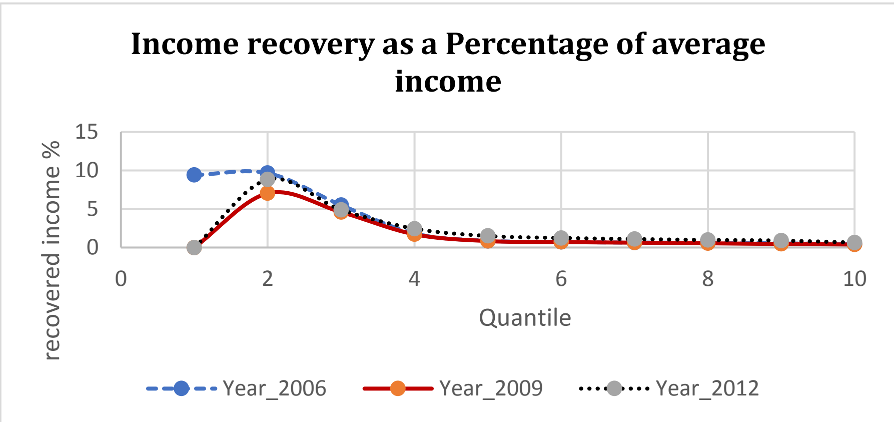


Figure 5

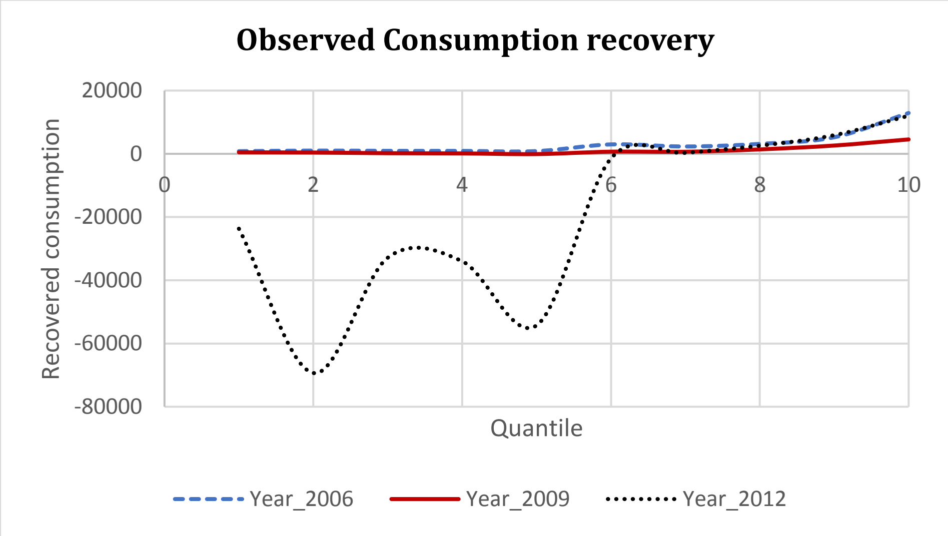
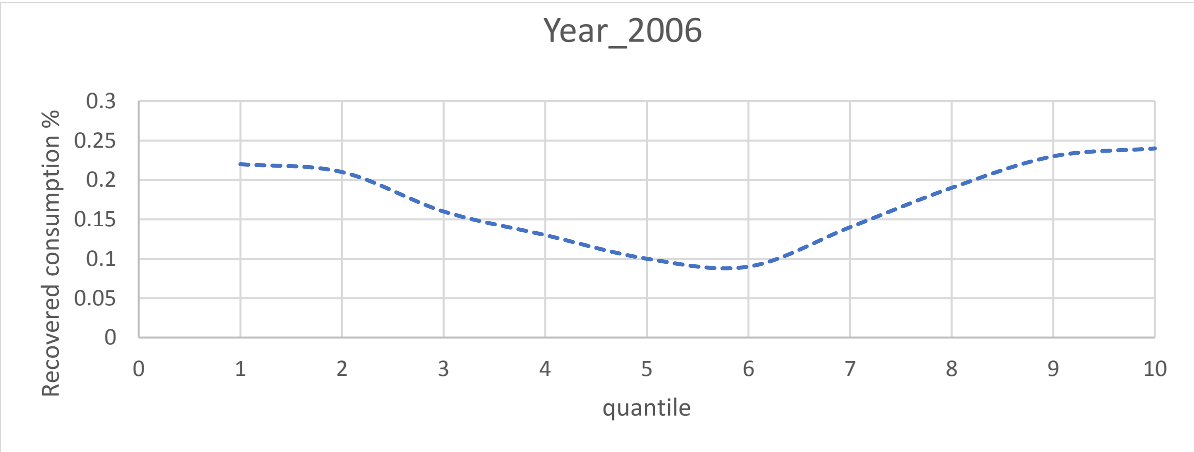


Figure 6 Consumption recovery as a percentage of average consumption



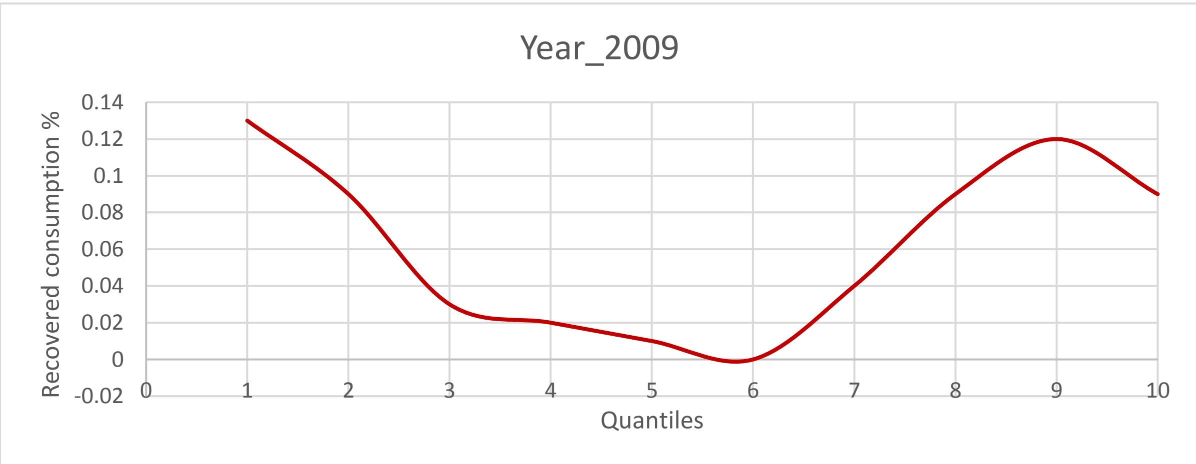


Figure 7

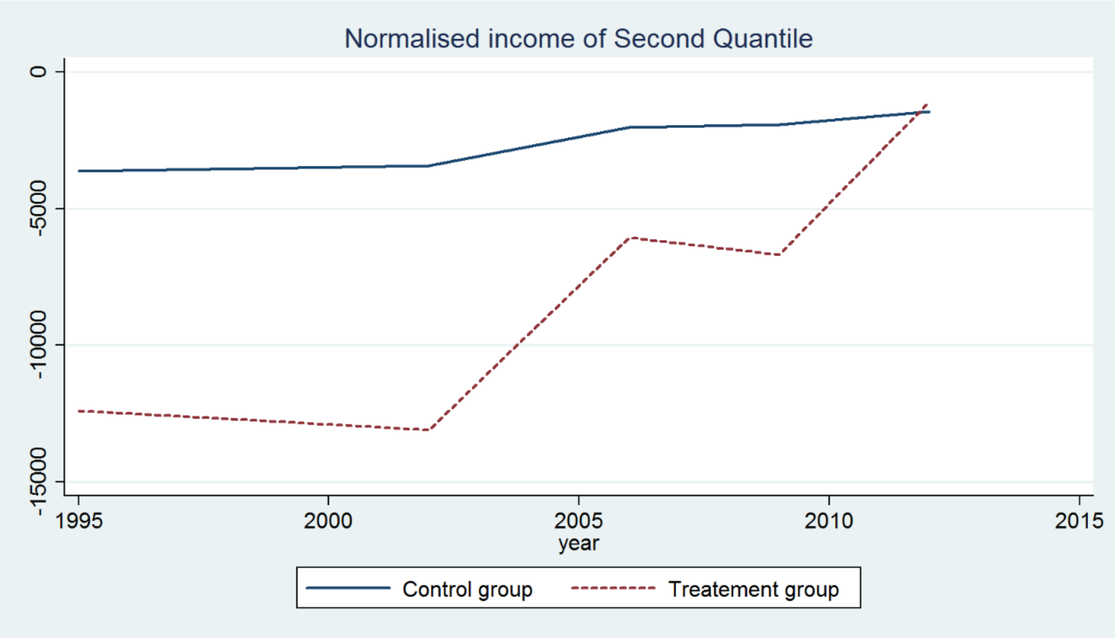


Figure 8

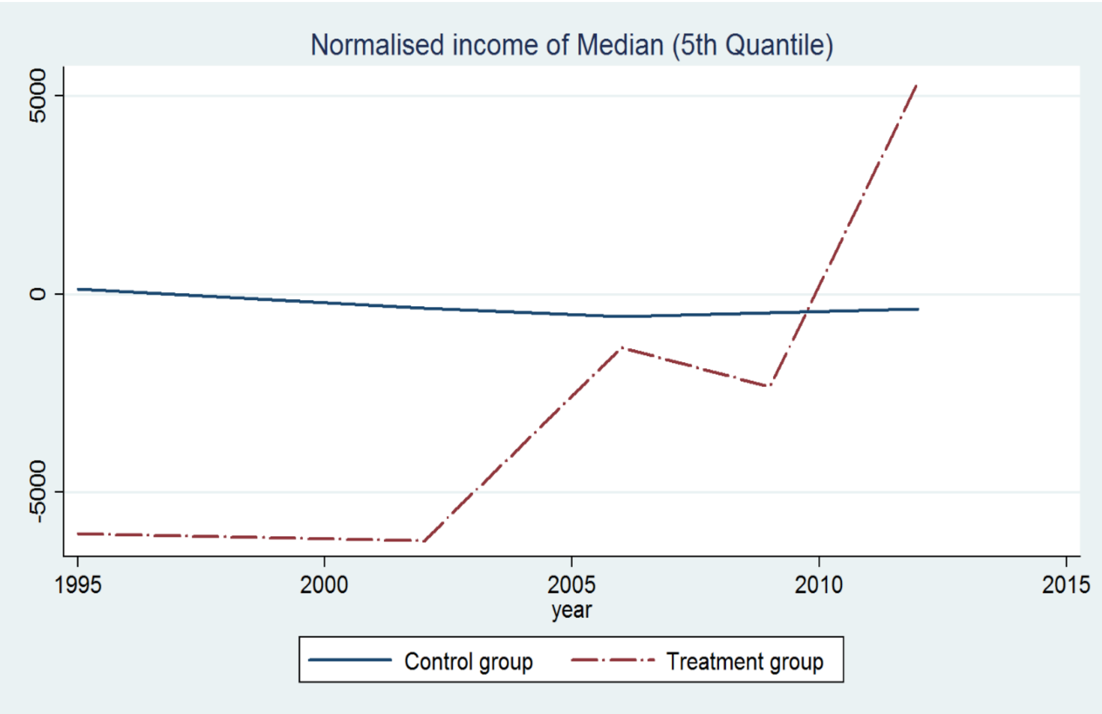


Figure 9

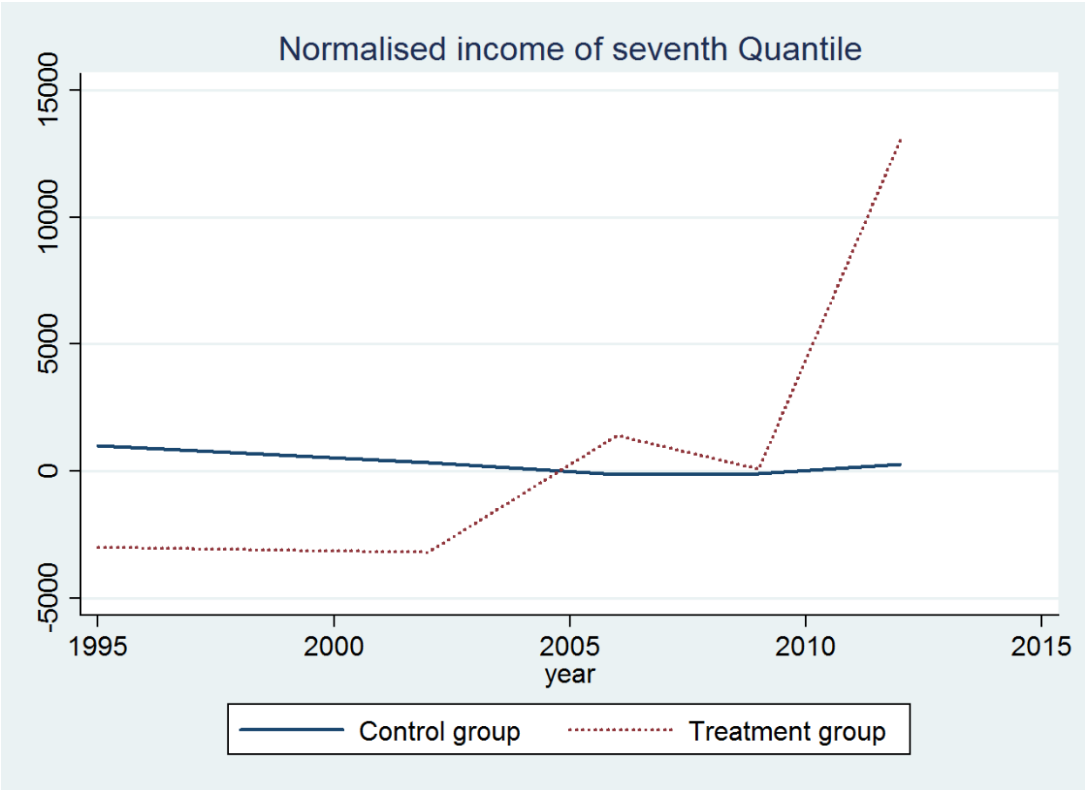


Figure 10

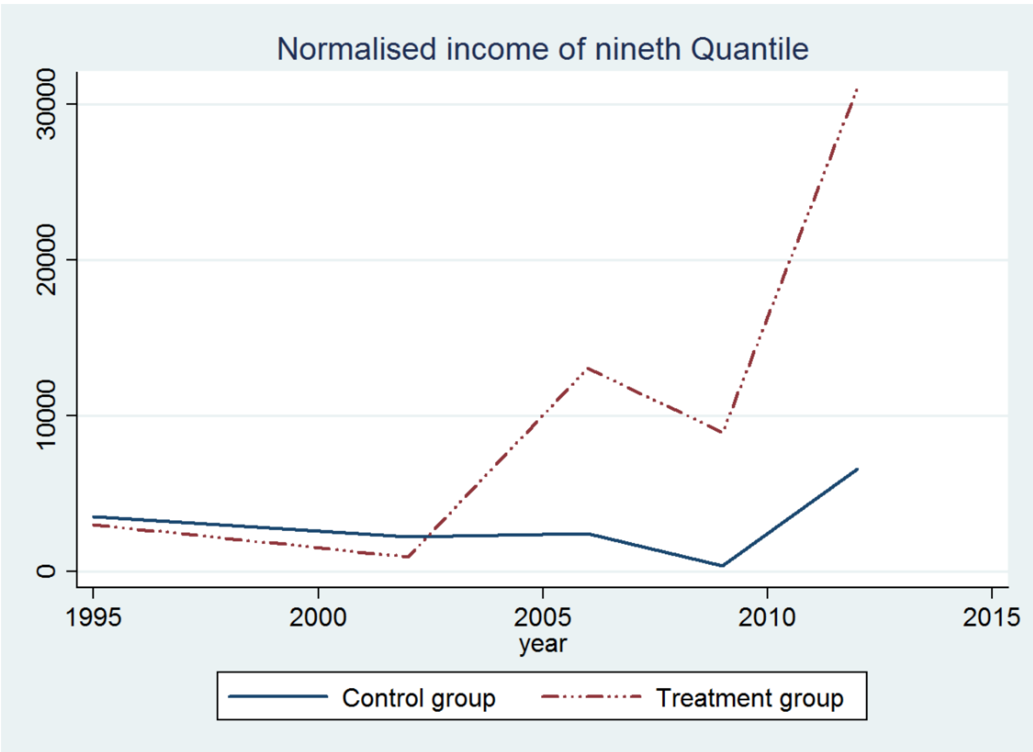


Figure 11

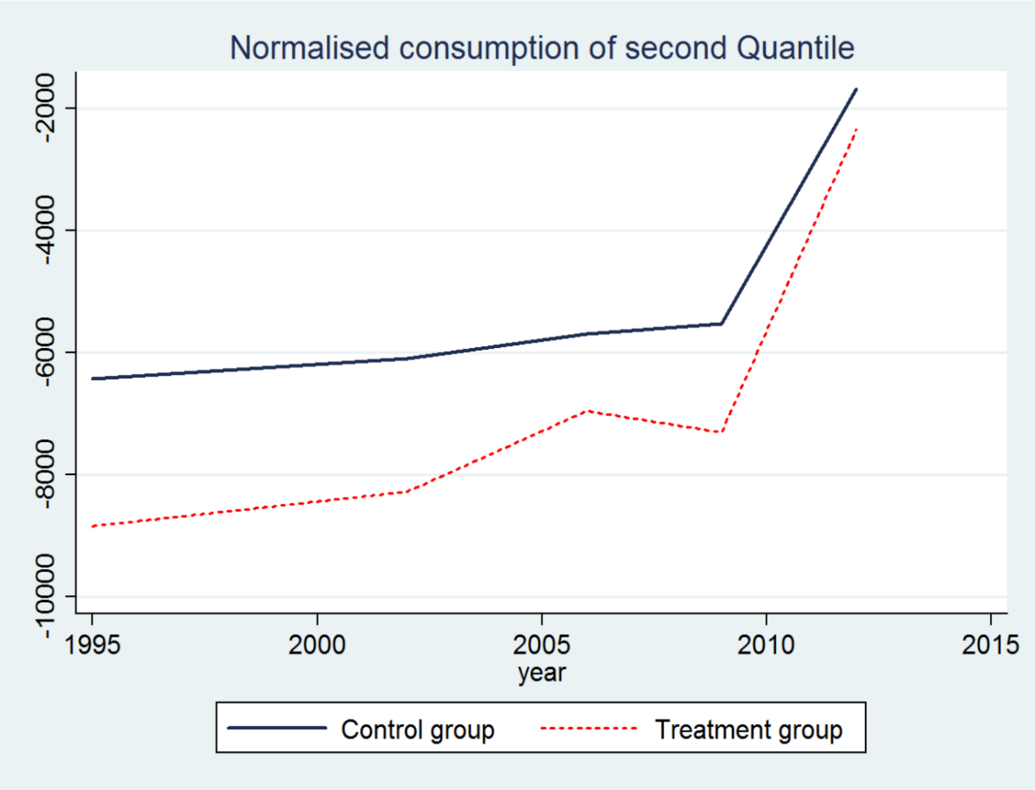


Figure 12

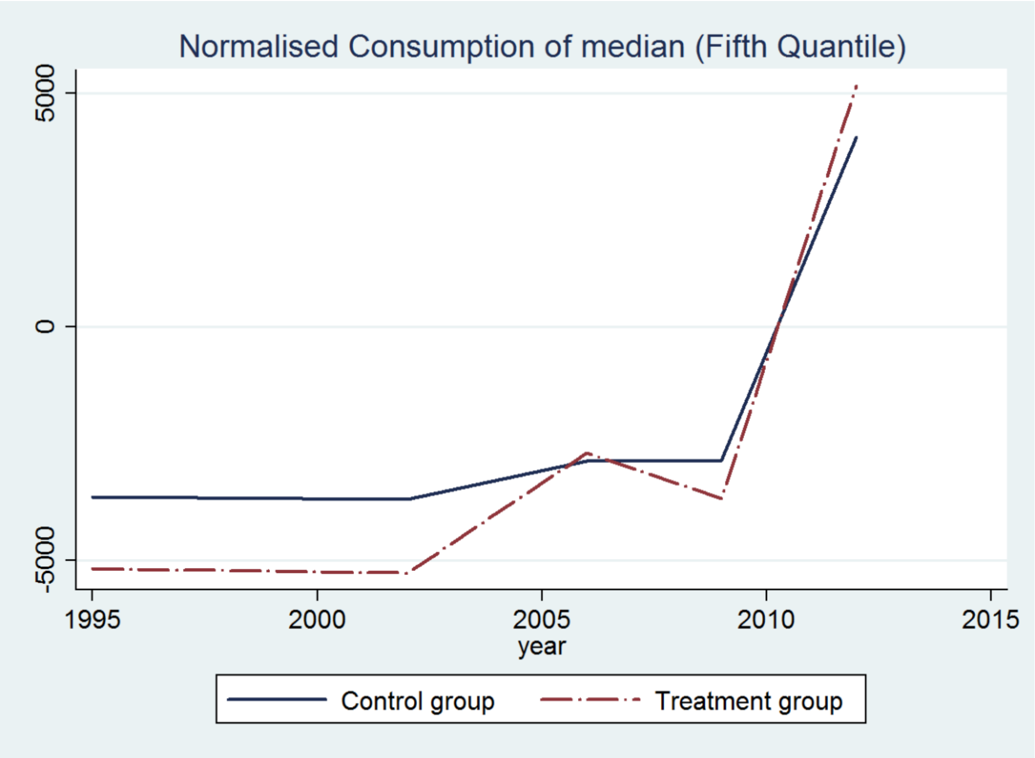


Figure 13

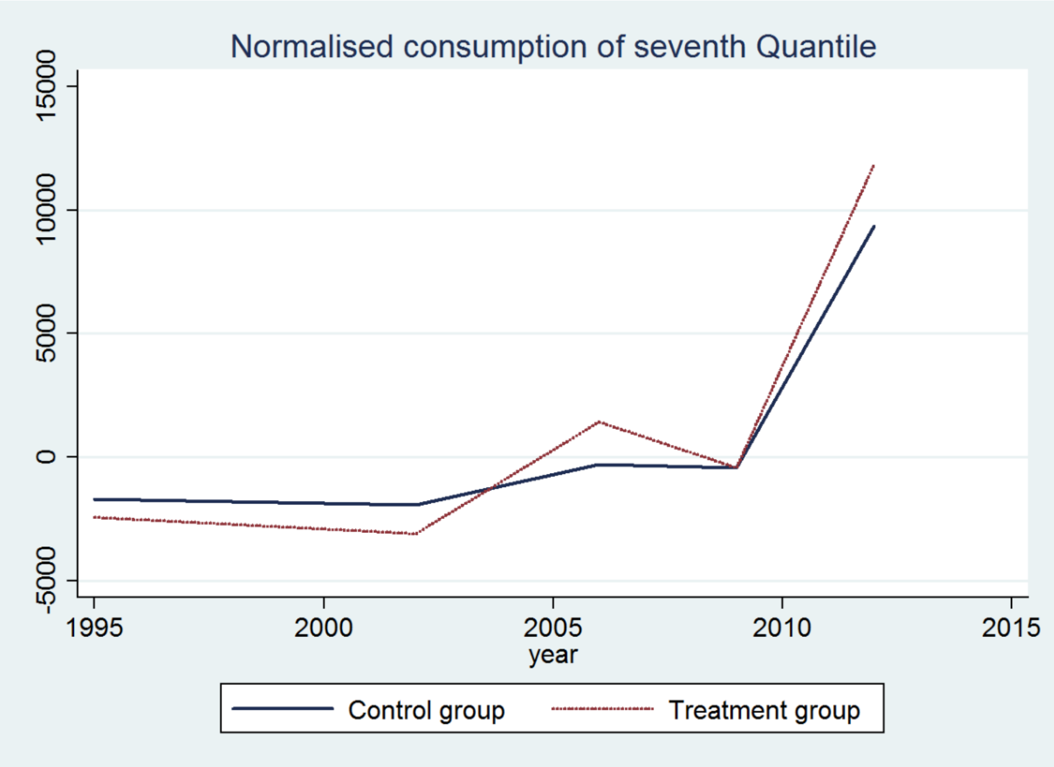
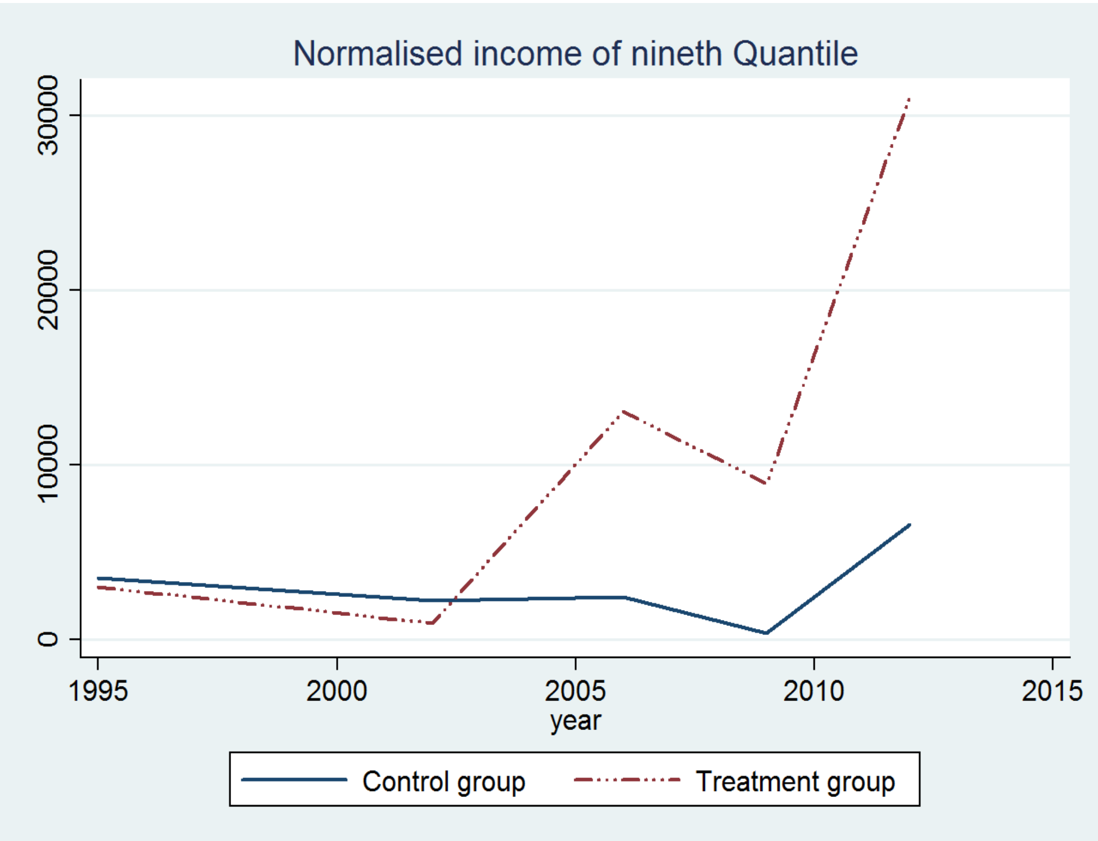


Figure 14



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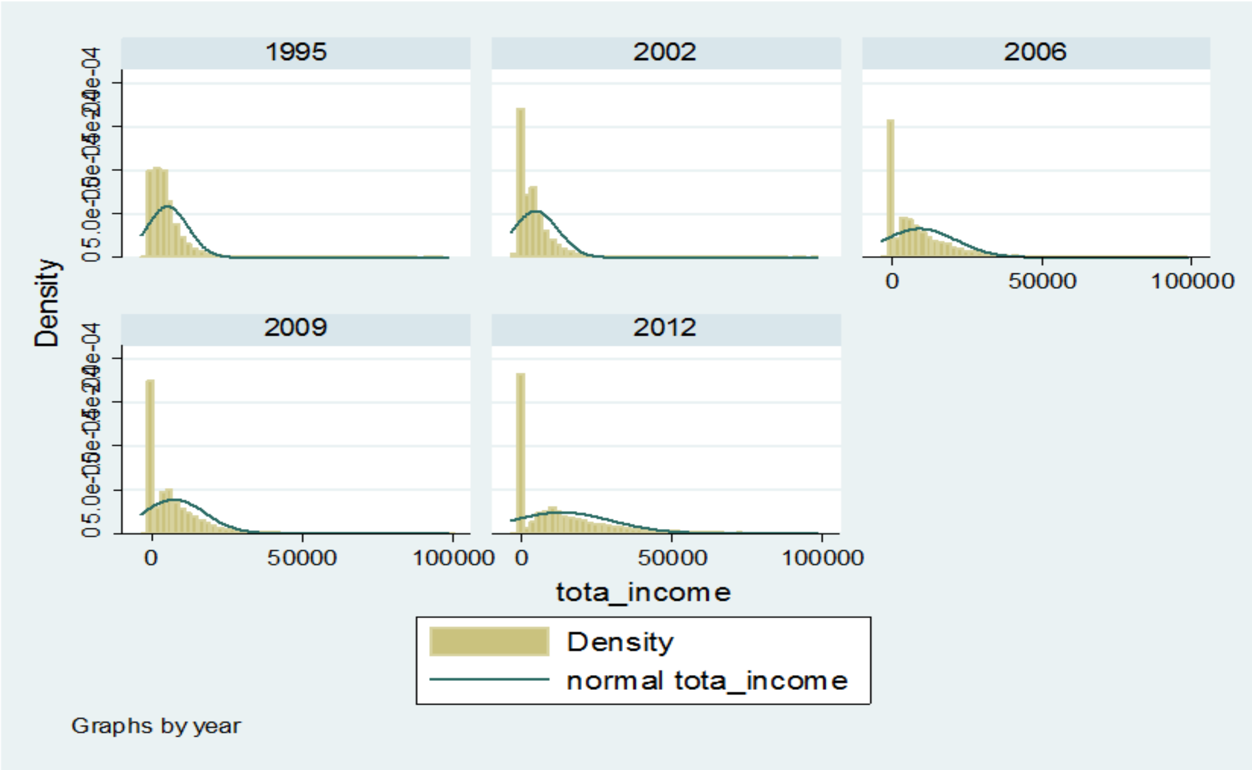
Appendices

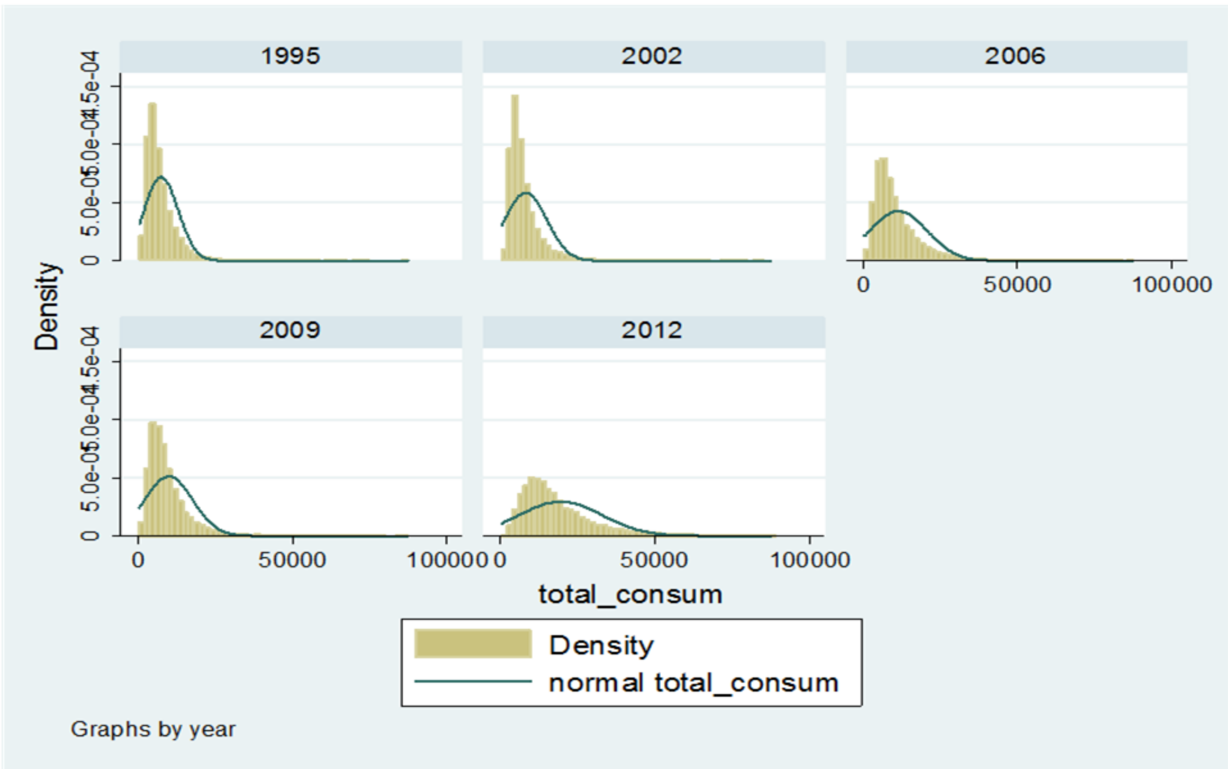
Appendix table 1: Components of household income and consumption

Income components	Description	1995 2006 2009 2012	2002
Paid income	Income from paid employments (wage/salaries, commissions, bonus, arrears)	√	√
Agricultural Income	Income from agricultural activities including value of produce consumed by the household	√	√
Non-agricultural Income	Income from non-agricultural activities including value of products consumed by the household	√	√
Remittance	Local and foreign remittance	√	√
Transfers	Receipts of government transfer payment, disability and relief payments	√	√
Dividends	Dividends and interests	√	√
Rents & other income	Property rents and other cash receipts	√	√
Ad hoc income	Loans taken, sales of assets, withdrawal of savings, income received from welfare societies, repayment of loans given, insurance compensations, lottery and other adhoc gains	√	X
Income components	**Description**		
Food	Value of consumed food of the household members excluding boarders and servants		
Non food	Household expenditure on housing fuel and light, personal care, health, transport and communication, education, recreation and cultural activities, nondurable household goods, household services (laundry, grinding etc.), clothing textiles and footwear, durable household goods. Non consumption expenses: Savings, payment of Insurance, debt, income tax, contributions to trade unions, thrift societies and social security payments (provident fund), expenses on social activities, donations, loans given.		
Servants	Expenses on servant's food and non-food consumption.		

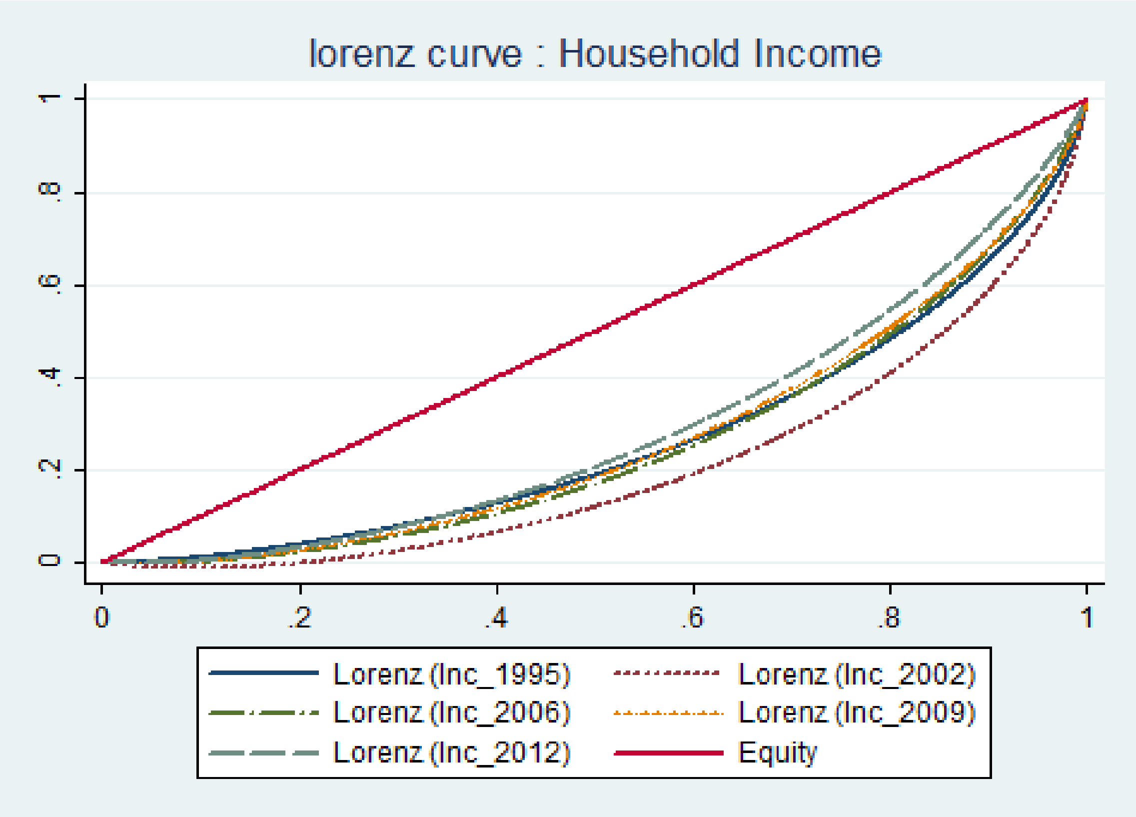
Appendix figure 1: Distribution of income



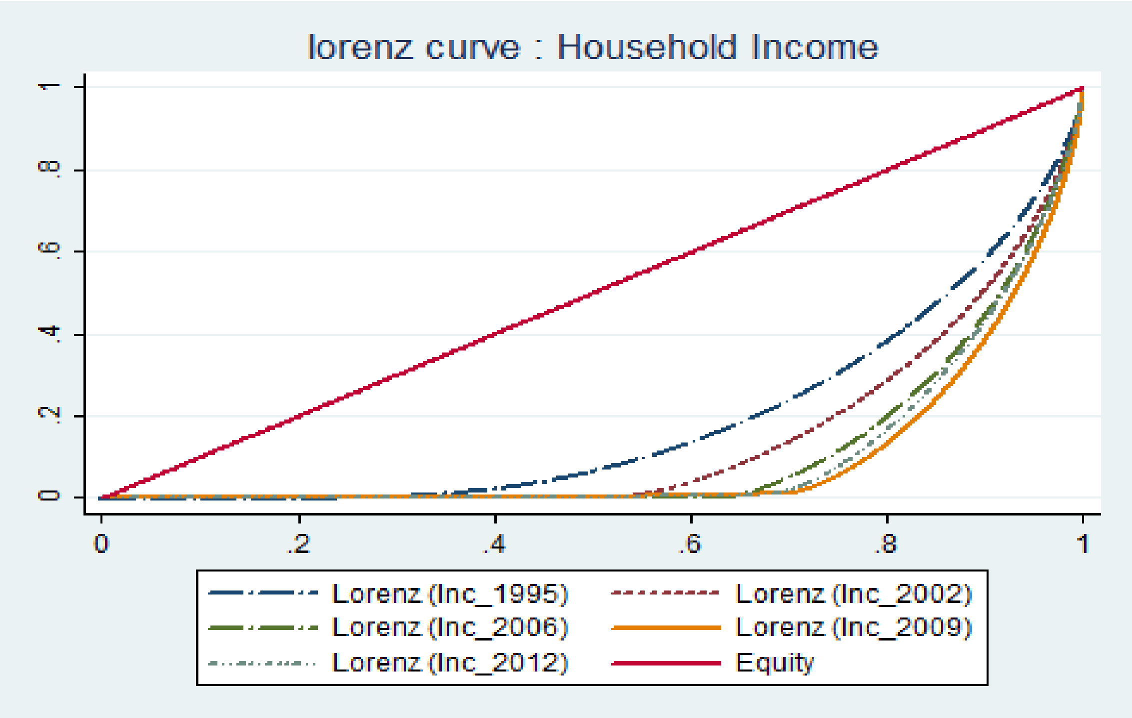
Appendix figure 2: Distribution



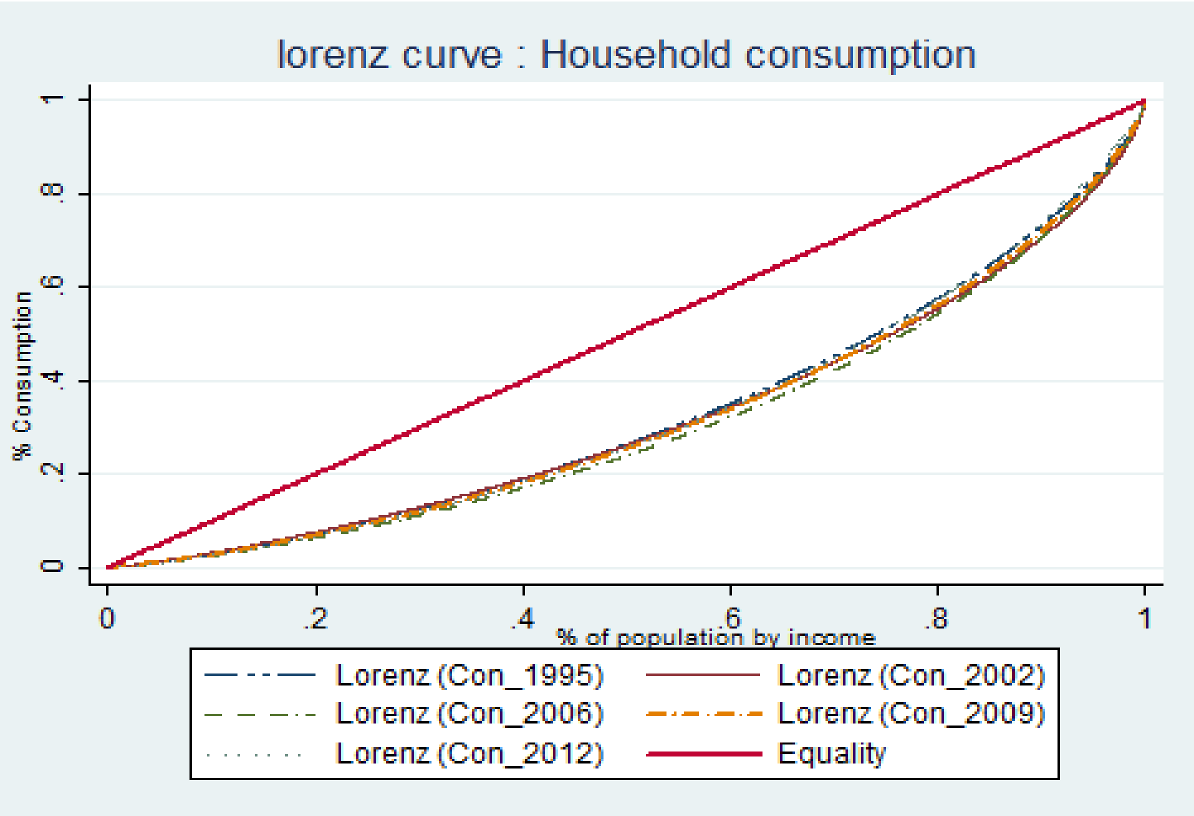
Appendix figure 3: Income Lorenz curve of Treatment group



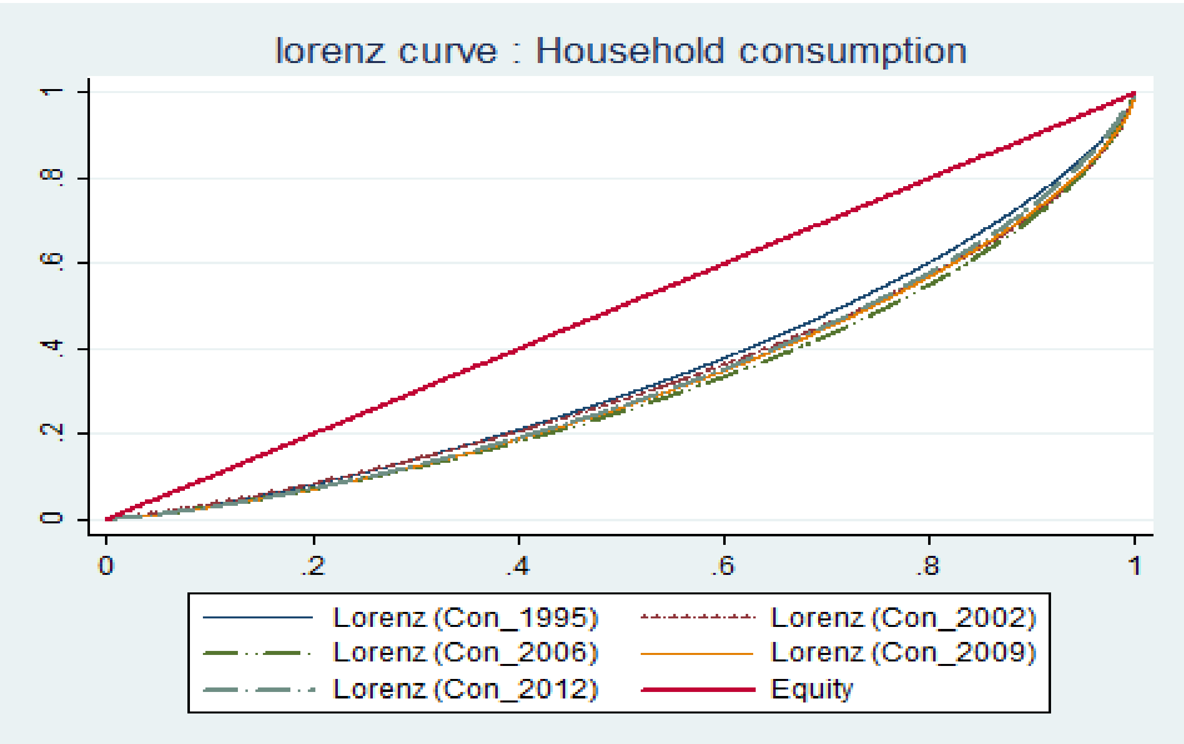
Appendix figure 4: Income Lorenz curve of Control group



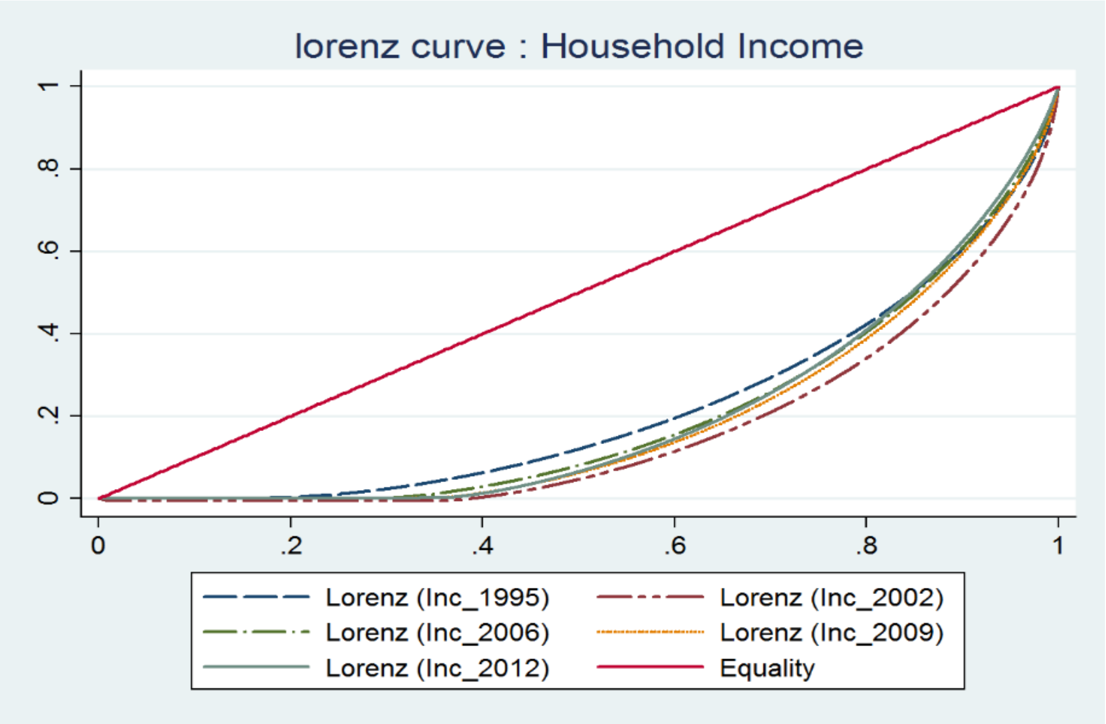
Appendix figure 5: Consumption Lorenz curve of Treatment group



Appendix figure 6: Consumption Lorenz curve of Control group



Appendix figure 7: Lorenz curve for all districts -Income



Appendix figure 8: Lorenz curve for all districts -Consumption